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News on Inflation and the Epidemiology of Inflation Expectations*

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Abstract

This paper examines the nexus between news coverage on inflation and households' inflation expectations. In doing so, we test the epidemiological foundations of the sticky information model (Carroll, 2003, 2006). We use both aggregate and household-level data from the Survey Research Center at the University of Michigan. We highlight a fundamental disconnection between news on inflation, consumers' frequency of expectation updating and the accuracy of their expectations. Our evidence provides at best weak support to the epidemiological framework, as most of the consumers who update their expectations do not revise them towards professional forecasters' mean forecast.

JEL classification: C53, D84, E31

Keywords: Inflation; Survey Expectations; News; Information Stickiness

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1 Introduction

The rational expectations revolution that has swept through the economics profession in the 1970s has shaped macroeconomic modelling ever since. Nevertheless, rational expectations have often been criticized based on their inadequacy to account for a realistic process of economic forecasting. In response to this criticism, recent years have borne witness to alternative theories of expectation formation, whose common trait consists of relaxing the set of strong assumptions imposed by the rational expectations paradigm. One of such novel approaches assumes that information is sticky and disseminates slowly throughout the population, so that economic agents revise their expectations periodically. Carroll (2003, 2006) (henceforth, Carroll) has put forward an epidemiological mechanism of expectation formation, according to which consumers update their expectations from the media, which are assumed to transmit professional forecasters' projections. The resulting framework is consistent with the intuition behind the sticky information model of Mankiw and Reis (2001, 2002).

Carroll examines inflation and unemployment forecasts collected by the University of Michigan's Survey Research Center. He shows that households revise their expectations towards the mean forecast from the Survey of Professional Forecasters, which he claims to be rational. The estimated absorption rate is rather low, with only a fourth (third) of the agents updating their inflation (unemployment) forecasts in every quarter.[1] He also provides empirical support to a main implication of the model, that is greater news coverage induces 'more rational' household forecasts. In fact, he shows that higher dissemination of news narrows the gap between the mean forecast from the Michigan Survey and that of professional forecasters.

This paper tests the epidemiological theory of expectation formation. From a methodological viewpoint, one of its main novelties consists of exploiting both aggregate and household-level data from the Michigan Survey. We primarily focus on Carroll's corollary that more news stories imply that people are better informed and produce better forecasts. To this end, we complement Carroll's index of newspapers coverage with Michigan Survey data on consumers' perception of favorable and unfavorable price developments in the period before the interview. These data allow us to compute a direct measure of the flow of news on prices that consumers have heard,

[1] Doepke et al. (2008) estimate Carroll's sticky information model of inflation expectations with data from Italy, Germany, UK, and France. They propose two alternative parameterizations of the sticky information model that differ in the stationarity assumptions about the underlying series. On average, European households revise their forecasts once every 18 months when stationarity applies. Otherwise, the VECM analysis shows that expectation updating takes place on a yearly basis.

as opposed to the index of newspapers coverage, which is not necessarily informative about the actual degree of receptiveness to publicly available information on prices. A surprising result is that both available and perceived news stories do not help at restricting the forecast gap between consumers' mean forecast and that of the professional forecasters, but rather widen it. Once we account for the content of the information that disseminates throughout the population, it turns out that unfavorable news (i.e., higher prices) exert a (positive) impact on the forecast gap, while favorable news (i.e., lower prices) have either no statistically significant impact or weakly contribute at reducing consumers' expectation bias. Overall, these results stand in sharp contrast with the theoretical apparatus put forward by Carroll.

The analysis with household-level data represents the core of the paper. We show that an average of about 75% of the respondents revise their inflation forecasts with respect to their first interview. This figure is considerably greater than the average fraction of respondents that have heard some news on prices (i.e., 5.8%). Also the absorption rate estimated by Carroll is considerably lower than the updating frequency we derive from household-level data. The micro-data from the Michigan Survey give us the opportunity of addressing this inconsistency and examining the epidemiological foundations of the sticky information model in greater detail, as they contain explicit information about the size and direction of consumers' expectation updating. We distinguish between respondents that adjust their forecasts towards and away from the professional forecasters' mean expectation. Surprisingly, survey participants split evenly in the two categories. Most importantly, accessing some recent information on prices does not necessarily reflect into more accurate forecasts, though it certainly raises the chances that consumers revise their expectations. Nevertheless, expectation updating does not systematically occur in the 'right' direction. These results are generally in line with the tendencies reported by Curtin (2005) in the analysis of both time-series and panel data from the Michigan Survey, though no information about news on prices is exploited in this study.[2]

Our analysis suggests that just a small fraction of consumer forecasts can be explained according to the epidemiological model. Moreover, it appears that households do not make the best use of the information they perceive, as they persistently deviate from professional forecasters' mean expectation, displaying no tendency to adjust their forecasts appropriately. One possible interpretation is that news transmitted by the media distort consumers' expec-

[2] According to this study, consumers do not efficiently use all available information and display staggered updating of their information set. Moreover, increases in the rate of inflation have a much larger impact than declines on inflation expectations.

tations, as they may contain judgmental assessments of professional forecasters' views. As a consequence, media reports could be biased and the epidemiological mechanism results as a channel that transmits distorted expectations. This factor could also explain why the degree of perception of unfavorable news on prices is significantly higher than that of favorable ones, and why the accuracy of consumers' expectations decreases in the volume of negative news being perceived. We believe these results should lead academics and policy makers altogether to reconsider the role of information dissemination in stimulating consumers' expectation updating. Most importantly, they should serve as a useful guideline to envisage communication strategies and channels capable of ensuring that private expectations are well anchored.

The remainder of the paper is laid out as follows: Section 2 describes the data; Section 3 explores the nexus between expectation updating and news, stressing the discrepancies between available and perceived news on prices; Section 4 explores household-level data from the Survey of Consumer Attitudes and Behavior. Section 5 concludes.

2 Data and Preliminary Evidence

We employ both aggregate and household-level data, though greater emphasis will be posed on the micro-econometric evidence. Household-level data contain information on a wide range of factors that influence consumers' expectations. As such, they allow us to explore the process of expectation updating in greater detail. In this section we describe the key features of the dataset and report some preliminary evidence on households' and professional forecasters' inflation expectations, as well as on the newspapers index proposed by Carroll and a novel measure of perceived news on prices.

2.1 Inflation Expectations

In the estimation of his model Carroll proxies household expectations with the mean inflation forecast from the Survey of Consumer Attitudes and Behavior, which is conducted by the Survey Research Center (SRC) at the University of Michigan. The Michigan Survey (henceforth, MS) has been available on a monthly basis since January 1978.[3] The short rotating panel design represents its main peculiarity: 40% of prior respondents are re-interviewed in every round,

[3] Over the whole sample, the survey covers a monthly average of 575 households, with a peak of 1479 respondents in 1978M11 and a minimum of 492 in 1992M11. A montly average of about 500 respondents has been inteviewed since 1987M1.

the remaining 60% being initial interviews from a random sub-sample of the telephone-owning mainland US population. Two relevant questions about expected changes in the price level are addressed to each participant: (i) first, they are asked whether they expect prices to go up, go down or stay the same in the next 12 months; (ii) second, they are asked to provide a quantitative statement about the expected change.[4]

As to professional forecasts, Carroll employs the mean inflation expectations from the Survey of Professional Forecasters (henceforth, SPF). The SPF, currently conducted by the Federal Reserve Bank of Philadelphia, has collected and summarized forecasts from leading private forecasting firms since 1968. The survey questionnaire is distributed once a quarter and asks participants for quarter-by-quarter forecasts, spanning the current and next five quarters.[5]

Insert Figure 1 here

The present study explores both aggregate and household-level data from the MS. The analysis at the aggregate level (Section 3) relies on quarterly data over the time window 1978Q1-2011Q2, while Section 4 reports evidence based on MS monthly micro-data data over the 1978M1-2011M2 period.[6] In the analysis at the aggregate level we take the MS and SPF mean forecasts as indicators of central tendency in inflation forecasting, so as to be coherent with Carroll's framework.[7,8] Figure 1 reports household and professional mean forecasts against CPI inflation.[9] Both surveys under-predict rising inflation in the first part of the sample, though their predictive accuracy improves remarkably during the subsequent disinflation. This is probably due to the credibility the Federal Reserve had acquired in the early 1980s, when the Federal

[4] If a respondent expects prices to stay the same, the interviewer must make sure she does not actually expect that prices will change at the same rate they have changed in the past 12 months.

[5] The SPF was previously carried out as a joint product of the National Bureau of Economic Research (NBER) and the American Statistical Association (ASA) on a wide variety of economic variables, including GDP growth, various measures of inflation and the rate of unemployment. For more details on the SPF, see Croushore (1998).

[6] The SPF forecast of CPI inflation is only available from 1981Q3. Therefore, from 1978Q1 to 1981Q3 we proxy the CPI inflation mean forecast from the SPF with the GDP deflator mean forecast. The two series are generally very close. However, for robustness purposes and to exclude the disinflation at the beginning of the sample and the ongoing period of financial and macroeconomic turmoil, Appendix A replicates the entire analysis on the 1984-2004 sub-sample. The results are virtually unchanged.

[7] One could argue that the median is less sensitive to outliers. In fact, cross-sectional variation of forecasts in the MS is substantial, with some unplausible responses. Moreover, Thomas (1999) shows the median of the MS to be a better forecaster than its mean. Nevertheless, Carroll's framework delivers predictions only for the mean and not for the median. For completeness, we replicate the analysis at the aggregate level using the median forecasts from the two surveys. Additional results are available in Appendix C and show no qualitative difference with respect to the main results reported in the paper.

[8] Given the presence of some implausible responses it is advisable to exclude outliers. Curtin (1996) shows that alternative truncation rules lead to nearly unchanged results. In the analysis of household-level data we opt for a truncation at -5% and +30%: this yields 228,837 interviews over the 1978M1-2011M2 period.

[9] Inflation expectations carried out at time t are graphed at the realized date (i.e., $t+4$), so as to enhance comparability with the forecast target.

Reserve System was headed by Paul Volcker. From 1984 onwards expectations appear reasonably anchored, although they often fail to match periods of low inflation and, most notably, the 2009Q1-2009Q3 deflation.

2.2 News on Inflation

A direct implication of Carroll's view is that more news stories should imply that people are better informed and produce better forecasts. He proposes a formal statistical test of whether greater news coverage is associated with 'more rational' household forecasts. The econometric model employed to test this hypothesis is at the core of our analysis and requires reliable indicators of the flow of news on inflation the public is confronted with. Carroll computes a yearly index of the intensity of news coverage in the New York Times and the Washington Post. We compute a similar index for each newspaper and each quarter since 1980Q1 (i.e., the year that both newspapers have been included in the LexisNexis database), searching for stories that contain words beginning with the root 'inflation' (so that also words like 'inflationary' or 'inflation-fighting' would be detected). For each newspaper, the number of stories is then converted to an index by dividing the number of articles about inflation in a given quarter by the total number of articles in the same quarter.[10]

We complement the newspapers index with a measure of the actual perception of new information about prices. This choice is motivated by a number of important considerations. The accuracy of a proxy based on the intensity of news coverage on national newspapers can be questioned on different grounds. Blinder and Krueger (2004) suggest that consumers mostly rely on information about inflation from the TV, followed by local and then national newspapers.[11] It is also plausible to expect that the volume of news about inflation does not necessarily match the flow of information that is actually assimilated by the public. In fact, a non-trivial discrepancy could result from the interplay of two mutually reinforcing effects: (i) news from the media do not necessarily reach the public uniformly and (ii) the connection between news and inflation expectations is likely to be affected by consumers' receptiveness to such news and the capacity to process new information. Indeed, Sims (2003) emphasizes the presence of information-processing

[10] A potential problem connected with this type of search is that the resulting index may include articles that do not primarily cover US inflation. Thus, we test the robustness of this methodology by restricting the search to articles that cover just US inflation. Moreover, we exclude articles with less than 120 words, so as to rule out short comments and summaries, searching for words beginning with the root "inflation" that are located either in the headline or among the "index terms". The resulting index yields to virtually unchanged evidence.

[11] It should also be stressed that over the last decade the internet has probably become a main source of news about various economic statistics.

constraints that could be compatible with such inefficiencies. In light of these considerations, it is advisable to complement the analysis with a variable that accounts for consumers' actual perception of the information reported in the media. Household-level data from the MS allow us to compute the fraction of respondents that have heard of recent changes in prices. Information about the content of such news is also available, with the survey participants indicating whether they have heard about positive or negative changes. Specifically, the following question is addressed to each household: "During the last few months, have you heard of any favorable or unfavorable changes in business conditions?"[12] In case of an affirmative response, a second question is asked: "What did you hear?" To address this query, the respondent is presented with a number of options regarding the type of business conditions she might have heard about, such as government, unemployment, prices, consumer demand, stock market, credit, trade deficit. She is allowed to name at most two of these options. Should prices be one of the selected options, she can reply either (i) "Favorable News: Lower Prices" or (ii) "Unfavorable News: Higher Prices."[13,14] It is important to mention that different perceptions about price movements could result both from the content of news reports being released through the media, as well as by the tone of the assessment and judgement about news being reported. In fact, Lamla and Lein (2008) suggest that newspapers may have an incentive to favor bad news over good ones, so as to catch more attention from the readers and increase their sales. The analysis presented in the remainder of the paper provides statistical and econometric support to this claim.

Insert Figures 2 and 3 here

Figure 2 reports the fraction of MS respondents that have heard news about prices, together with the newspapers index and CPI inflation. The two news-related series are poorly correlated. Moreover, the newspapers index displays weaker co-movement with the rate of inflation, as compared to our measure of 'perceived news'. The latter is more volatile, especially when abrupt changes in the rate of inflation occur, though in the last part of the sample it displays sizeable

[12] Consumer sentiment indeces as those that can be derived from household-level data on the perception of business conditions have been usefully employed in various studies. For instance, Souleles (2004) presents an application on consumption behavior.

[13] Should the interviewer perceive that the respondent has an uncorrect understanding of the question on perceived changes in prices, a further question is asked that aims at making sure that the responses "Favorable News: Lower Prices" and "Unfavorable News: Higher Prices" are interpreted correctly.

[14] MS respondents primarily report about news on unemployment, followed by news on the government (elections) and then prices. It is important to stress that 41% of the respondents report having heard no news at all and that in 28% of the cases only one option is reported. This is to say that, on average, only 31% of the respondents are confronted with a potentially binding limit of two options. Therefore, though some underreporting may affect our measure of perceived changes in prices, this is not likely to be induced by the limit of two responses.

fluctuations that neither actual inflation nor the newspapers index present. This probably reflects higher uncertainty characterizing consumers' information during the recent period of marked macroeconomic and financial turmoil. When looking at the perceived tone of the news consumers have heard (Figure 3), it can be noted that the fraction of consumers that have heard favorable news almost constantly lie below the fraction of those that report unfavorable news. The latter proportion of respondents is more volatile and tends to peak when inflation accelerates. As expected on a priori grounds, the percentage of agents reporting favorable news is negatively (yet weakly) correlated with the rate of inflation. The sign of this correlation is reversed when considering the fraction of respondents that have heard negative news, which indicates that households pay attention to news coverage mostly during periods characterized by relatively higher and more volatile inflation.[15] According to Hamilton (2004) and Soroka (2006), a common finding in literature on news coverage is that there is more reporting of bad news than good ones. In fact, this type of asymmetry is in line with the prospect theory pioneered by Kahneman and Tversky (1979), as agents tend to manifest higher receptiveness towards bad news on prices, as compared to good news.

3 News and Expectation Updating: Evidence from Aggregate Data

According to the epidemiological foundations of the sticky information model, consumers update their forecasts from news reports, which are influenced by the expectations of the professional forecasters.[16] The key assumption is that news spread slowly across agents, reaching only a fraction of the population in each period. Carroll examines his model's ability to explain the MS data by estimating an equation of the form:

$$\pi^C_{t+4|t} = \alpha_1 \pi^F_{t+4|t} + \alpha_2 \pi^C_{t+3|t-1} + v_t, \tag{1}$$

where $\pi^C_{t+4|t}$ denotes the time t mean MS forecast of time $t+4$ inflation and $\pi^F_{t+4|t}$ is the SPF mean forecast. We estimate (1) by OLS and report the estimation results in Table 1. Overall

[15] Note that in the last part of the sample higher volatility in the measure of (perceived) unfavorable news is not accompanied by higher volatility in the rate of inflation. Such a de-linking in the behavior of the two series probably reflects the emergence of additional determinants of consumers' receptiveness to news about inflation, as well as the substantial increase in the volume of economic reporting on different aspects of the ongoing financial and macroeconomic turmoil.

[16] Mankiw and Reis (2001, 2002) envisage a similar framework. They assume that agents update their forecasts only occasionally, due to the presence of an explicit cost to obtain and process information.

our evidence is qualitatively in line with Carroll, as the rate of absorption we estimate implies that about a fourth of the MS participants update their forecasts in every quarter. An important difference with the benchmark study is that the proposition $\alpha_1 + \alpha_2 = 1$ can be rejected at standard levels of statistical confidence. Thus, we reject the key model's prediction that households' mean expectations should be a simple weighted average between the current 'rational' (or newspaper) forecast and last period's mean inflation expectations.[17] We also expand the set of regressors in Equation (1) with the most recently published annual inflation rate as of time t. As in Carroll, the past inflation rate exerts a negative impact, though its coefficient is not statistically significant.

Insert Table 1 here

The results so far are somehow supportive of the epidemiological process of expectation formation. However, an indirect test of the model's ability to fit the data can be envisaged by comparing the estimates of α_1 in Equation (1) with the actual degree of receptiveness to news displayed by the MS participants. In this respect survey data reflect a higher degree of information stickiness, as compared with the indirect measure of updating frequency obtained by Carroll. On average, only 5.8% of the interviewees report having heard news about prices in each quarter. Such a discrepancy emphasizes the need to distinguish between 'available' and 'perceived' news for a reliable assessment of the relationship between news coverage of inflation, staggered updating of expectations and consumers' predictive accuracy. To this end, we examine the corollary that greater news coverage should be associated with 'more rational' household forecasts. As a formal procedure to test for this, Carroll fits an OLS regression of the squared distance between the MS and SPF forecasts, $GAPSQ_t = \left(\pi^C_{t+4|t} - \pi^F_{t+4|t}\right)^2$, on the intensity of news coverage of inflation, $NEWS^N_t$:

$$GAPSQ_t = \gamma_0 + \gamma_1 NEWS^N_t + \mu_t. \tag{2}$$

A negative γ_1 implies that an increase in the volume of news induces an alignment of consumers' expectations to the SPF mean forecast. We propose a general model to account for the joint

[17] Nunes (2009) finds similar evidence.

effect of perceived and available news, as well as for their potential interaction:

$$GAP_t = \gamma_0 + \gamma_1 NEWS_t^N + \gamma_2 NEWS_t^P + \gamma_3 \left(NEWS_t^P \times NEWS_t^N\right) + \mu_t, \quad (3)$$

$$GAP_t = \{GAPSQ_t, GAPSQ_t^*\},$$

where $NEWS_t^P$ is the fraction of MS respondents that have heard news about prices. As exposed above, we interpret this measure as an explicit indicator of the actual flow of information assimilated by the public, as compared with the newspapers index employed by Carroll.[18] To test the robustness of our results we also consider an alternative measure of expectation bias, which depends on the distance between the time t MS mean forecast of inflation at time $t+4$ and CPI inflation at time $t+4$: $GAPSQ_t^* = \left(\pi_{t+4|t}^C - \pi_{t+4}\right)^2$. In fact, $GAPSQ$ does not account for the fact that professional forecasters may not form expectations rationally, as indicated by a number of studies (e.g., Roberts, 1998, Lanne et al., 2009 and Nunes, 2009).

Insert Table 2 here

Surprisingly, estimating (3) and various alternative specifications points to a positive and statistically significant relationship between the expectation gap and either measure of the flow of news on inflation (see Table 2).[19] Therefore, a rise in the fraction of 'informed' consumers increases the distance between the MS and SPF mean forecasts, a result that stands in sharp contrast with Carroll (2003). When accounting for the joint effect of $NEWS_t^P$ and $NEWS_t^N$, only the former exerts a positive impact on the expectation gap, while the coefficient attached to $NEWS_t^N$ is either not statistically different from zero or barely significant. Finally, we check whether any interaction is at work between newspapers' coverage and households' receptiveness to news about inflation, introducing the interaction term $NEWS_t^P \times NEWS_t^N$ in the set of regressors. The additional regressor explains most of the variability in $GAPSQ_t$, though its coefficient is only significant at the 10% level. As to $NEWS_t^P$ and $NEWS_t^N$, they both exert a

[18] Note that $NEWS_t^P$ proxies the amount of news heard before the inflation forecast is carried out. This allows us to avoid the impact of reverse causation.

[19] Importantly, we reach the same conclusions by regressing the expectation gap over a constant and the newspapers index $NEWS_t^N$. These results are not overturned if we consider the time window examined by Carroll (additional results are available, upon request, from the authors). By contrast, it should be noted that Carroll's estimates are not robust in this sense, as he shows that excluding the first year of the SPF mean forecast from the sample may affect the statistical significance of the estimated impact of news on the expectation gap. It should also be noted that Carroll uses a yearly index in regressions involving quarterly data. Our estimates do not suffer from this type of inconsistency, as we compute a quarterly newspapers index.

negative impact, though their coefficients are not statistically different from zero.[20] This comes as no surprise, given that both measures of news present positive correlations with $GAPSQ_t$. Nevertheless it should be noted that perceived news present greater correlation with either measure of prediction bias and dominate their correlations with the interaction term.[21]

3.1 Asymmetric Effects of Favorable and Unfavorable News on Prices

We now focus on a second dimension of the relationship between news on inflation and expectation updating, which consists of accounting for the perceived content of the news consumers have heard of. Doms and Morin (2004) show that media coverage is important in that it affects households' perception of the economy in at least three ways. First, media affects sentiment by informing consumers about economic data and professional opinions. Second, the greater the volume of news about the economy, the greater the likelihood that consumers update their expectations. These channels are explicitly at work in Carroll's framework. Doms and Morin (2004) point to a third channel, suggesting that consumers receive a signal about the economy through the tone of economic reporting.[22] This section is aimed at disentangling the differential impact that favorable and unfavorable news on prices may exert on consumers' forecast accuracy and the frequency at which they revise their inflation forecasts. We first examine the existence of potential asymmetries in the rate of absorption, comparing situations in which the volume of (perceived) negative news is greater than that of positive ones, and viceversa. The following equation is estimated by OLS:

$$\pi^C_{t+4|t} = \left[\alpha^U_1 \mathbb{I}_t + \alpha^F_1 \left(1 - \mathbb{I}_t\right)\right] \pi^F_{t+4|t} + \left[\alpha^U_2 \mathbb{I}_t + \alpha^F_2 \left(1 - \mathbb{I}_t\right)\right] \pi^C_{t+3|t-1} + v_t, \tag{4}$$

where $\mathbb{I}_t$ is an indicator function, whose value equals one when $NEWS^{P,U}_t > NEWS^{P,F}_t$ – i.e. when the fraction of MS respondents that report unfavorable news on prices ($NEWS^{P,U}_t$) is greater than the portion of those reporting about favorable news ($NEWS^{P,F}_t$) – and zero otherwise. The next step consists of disentangling the impact of unfavorable news from that of

[20] When assuming $GAPSQ^*_t$ as the dependent variable, the interaction term has no statistically significant impact, while $NEWS^P_t$ exerts a stronger positive impact than $NEWS^N_t$, whose effect is only significant at the 10% level.

[21] The correlation between $GAPSQ_t$ and $NEWS^P_t$ ($NEWS^N_t$) is about 60% (24%). Otherwise, $Corr\left(NEWS^P_t, GAPSQ^*_t\right)$ is about 57%, while $Corr\left(NEWS^N_t, GAPSQ^*_t\right)$ is not statistically different from zero. Table B1 in Appendix B reports pairwise correlations among the variables employed in the regression analysis of Section 3.

[22] According to Sims (2003), rational inattention provides an explanation why the tone and volume of economic reporting affect sentiment beyond the economic information contained in the reporting.

favorable ones on the distance between MS and SPF mean forecasts. The following equation is estimated:

$$GAP_t = \gamma_0 + \gamma_1^U NEWS_t^{P,U} + \gamma_1^F NEWS_t^{P,F} + \mu_t. \tag{5}$$

Insert Table 3 here

Estimating (4) returns no particular form of asymmetry in the way favorable and unfavorable news affect consumers' expectation updating (see Table 3(a)). The estimated rates of absorption do not vary significantly depending on consumers' perception and are quantitatively in line with the estimates of (1). By contrast, we detect some relevant asymmetries when exploring the impact of positive and negative changes in prices on consumers' expectation bias. Table 3(b) shows that while favorable news exert a negative – yet not statistically significant – impact on the expectation gap, unfavorable ones tend to enlarge it.[23] Thus, we cannot appreciate a negative impact of news on the expectation gap even when consumers' overall perception is more pessimistic and their forecasts should be more accurate, or at least reflect higher attentiveness to economic reporting. Also Lamla and Lein (2008) report similar evidence based on German data on inflation expectations, while Dräger (2011) obtains analogous results in the analysis of both expected and perceived inflation in Sweden. These facts certainly deserve to be examined in further detail. The next section investigates these issues with the support of household-level data.

4 News and Expectation Updating: Evidence from Household-Level Data

The MS household-level data provide us with a further opportunity to test Carroll's microfoundation of the sticky information model. To this end, we examine the nexus between individual-specific information on prices and expectation updating. We start by extracting the proportion of survey participants that have updated their inflation forecasts in the second interview: Figure 4 reports the resulting time-varying frequency of expectation updating, together with CPI inflation. The two series display positive co-movement, though the former is more volatile. It is interesting to note that, on average, expectation updating takes place at a faster pace when

[23] It is interesting to note that for the sub-sample 1984Q1-2004Q4 favorable news actually contribute at restricting the gap, while unfavorable news still exert a positive effect (see Table A3(b) in Appendix A).

inflation is higher and more volatile, as in the first part of the sample. Notably, the time-varying frequency reaches its maximum only in two episodes, namely March 1980 (i.e., the highest peak in the rate of inflation) and November 1989.[24]

On average, 74.9% of the respondents do update their inflation forecasts in the second interview. Among these, 53.2% (46.8%) adjust their expectations downwards (upwards).[25] Thus, the fraction of consumers that revise their forecasts is significantly greater than the proportion of those who have perceived news about inflation, as well as than the absorption rate estimated by Carroll. Further insights come from inspecting the direction of expectation updating. We compare the fraction of respondents that revise their expectations towards the SPF mean forecast with those who move further away in the second interview. Interestingly, households split evenly into these categories, with 50.8% of the participants revising expectations in the 'right' direction. The picture is virtually unchanged even if we consider 'informed' households: in this case, the percentage of those who update expectations towards the SPF benchmark is 49.6%.[26] We also compute the average forecast error for those consumers who update their expectations and those who do not, as well as for households who report some recent news on prices and those who do not (see Table 4). Surprisingly, the average forecast error is about 12% higher when consumers update their forecasts, no matter whether they are aware of some recent changes in prices. Table 4 also implies that the average forecast error is significantly higher when consumers report of recent changes in prices, as compared to when they do not.

Insert Figure 4 here

Insert Table 4 here

The key message we retrieve from the investigation of the household-level statistics is that having some information at hand does not necessarily reflect into more accurate forecasts. Armed with this preliminary evidence, a main task of our analysis is to examine in closer detail the interconnection between the degree of receptiveness to news about inflation and the probability

[24] In early 1980, Volcker's new FED policy began to bite. U.S. interest rates started to increase substantially, with the prime rate hitting 20% in April 1980. As to the second episode, this might reflect increasing fears of contraction in economic activity, as then happened in the early 1990s.

[25] Unless otherwise indicated, the proportion of MS participants we report in this section (conditional on alternative attributes) are statistically different at the 1% level of significance.

[26] We also consider expectation updating 'towards' the CPI rate of inflation. In this case only 50.5% of the MS interviewees that update their forecasts do revise them in the 'right' direction. This figure drops to 49% when we consider agents that have heard of changes in prices, though this fraction is statistically lower than 50% only at the 10% level of significance.

that households revise their expectations. We specify a binary response model of the process underlying expectation updating at the household-level. The following variable is defined:

$$z_i = \begin{cases} 1 \text{ if } z_i^* > 0 \\ 0 \text{ if } z_i^* \leq 0 \end{cases}, \ i = 1, 2, ..., N, \tag{6}$$

where z_i^* is the latent variable that accounts for consumers' expectation updating. Its discrete counterpart, z_i, takes value one if the ith respondent has updated her expectations from the first interview, and zero otherwise. Since individuals are interviewed only twice, the only reference term to determine whether expectation updating has taken place is represented by the response in the second interview. Thus, we avoid reporting the time-subscripts. The following latent process is assumed:

$$z_i^* = \alpha + NEWS_i^P \beta + NEWS^N \rho + \pi\delta + \pi^F \vartheta + \mathbf{x}_i \boldsymbol{\gamma} + u_i, \tag{7}$$

where α is a constant, $NEWS_i^P$ is an individual-specific indicator of news perception (which equals one if the interviewee has heard of recent changes in prices and zero otherwise), $NEWS^N$ indexes the intensity of news coverage, π denotes the last observed CPI inflation rate,[27] π^F is the mean forecast from the SPF, $\mathbf{x}_i$ is a vector of socio-demographic characteristics (such as gender, age, income, education, race, marital status, location in the US and some interaction terms) and u_i is normally distributed. A word of caution is in order before we proceed with the analysis. As described in Section 2, sample selection is designed so that not all initial survey respondents are re-interviewed. Moreover, though the SRC tries to ensure that first interviews are a random sub-sample of the population, not all respondents who are selected for a second interview agree to participate. We label the resulting drop off as 'interview attrition'. It is also possible to identify a fraction of respondents that participate in the second interview but do not provide a year-ahead inflation expectation. The resulting drop off is usually referred to as 'question attrition'. To account for these potential sources of bias, we implement the Heckman correction (Heckman, 1979), a procedure that offers a means of correcting for non-randomly selected samples.

Insert Tables 5 and 6 here

[27] We have also considered the possibility that consumers look at alternative inflation measures, such as average inflation over the 6 months re-interview period. However, we obtain neither qualitatively nor quantitatively different results.

The binary response framework provides some support to the sticky information paradigm. As shown in Tables 5 and 6, hearing news on prices on average increases the probability of revising inflation forecasts, no matter which news-related variable is considered.[28] Also current inflation and the SPF mean forecast exert a positive impact, though the latter seems to induce a stronger marginal effect on the probability of revising expectations.

The analysis of household-level data also confirms that an increase in the volume of (available or perceived) news widens the gap between household forecasts and the SPF mean expectation, as indicated by the impact of $NEWS^P_{i,t}$ in the following regression:

$$GAP_{i,t} = \alpha + NEWS^P_{i,t}\beta + \mathbf{h}_{i,t}\boldsymbol{\eta} + u_{i,t}, \tag{8}$$

$$GAP_{i,t} = \left\{GAPSQ_{i,t}, GAPSQ^*_{i,t}\right\}, \tag{9}$$

where $GAPSQ_{i,t}$ is the squared difference between the MS household-specific forecast and the SPF mean inflation forecast, $GAPSQ^*_{i,t}$ is the squared difference between the the MS household-specific forecast and CPI inflation (at the forecast horizon), $\mathbf{h}_{i,t}$ is a vector of all other covariates reported in Equation (7) and $\boldsymbol{\eta}$ is a vector of coefficients. Moreover, $u_{i,t} = v_i + \varepsilon_{i,t}$, where $v_i \sim N\left(0, \sigma^2_v\right)$ is an individual specific random effect, $\varepsilon_{i,t} \sim N\left(0, \sigma^2_\varepsilon\right)$ is the idiosyncratic component of the error term and $Cov\left(v_i, \varepsilon_{i,t}\right) = 0$. The results from the estimation of (8) are reported in Tables 7 and 8. Along with $NEWS^P_i$, also $NEWS^N$ contributes at widening both $GAPSQ_{i,t}$ and $GAPSQ^*_{i,t}$. This confirms the evidence obtained with aggregate data and reflects the fact that the average forecast error is significantly higher when consumers are informed of recent changes in prices, as displayed by Table 4. It is also important to note that only (perceived) unfavorable news exert a positive effect on the expectation bias, while perceiving favorable news does not seem to have a statistically relevant effect.[29] As suggested by Hamilton (2004) and Lamla and Lein (2008), a possible interpretation of these facts is that media coverage may carry some 'judgemental' assessment of professional forecasters' projections that eventually biases household forecasts.

Insert Tables 7 and 8 here

[28] Tables 5 and 6 report marginal effects for a representative agent with the following characteristics: white (non Hispanic), married, male, 40 years old, with a high school diploma, with an income in the middle quintile of the distribution and living in the North-Center of the US.

[29] Curtin (2005) employs household-level data and reports about asymmetric responses of inflation expectations to positive and negative changes in actual inflation. He interprets this evidence as signalling the possibility of an asymmetric response to changes in the perceived credibility of central banks. According to this view, increases in inflation will more promptly diminish the credibility of central banks, but declines in inflation will only slowly rebuild lost credibility.

The econometric and statistical analyses with the MS micro-data provide us with two elements whose coexistence is problematic for the internal consistency of Carroll's argument. On the one hand, hearing news about prices increases the probability that consumers update their expectations. On the other hand, even if consumers have heard of some recent changes in prices, expectations are not necessarily revised in the right direction. The last point in particular raises the problem of investigating in closer detail how expectations are actually revised. To address this issue we specify the following probit regression:

$$\Pr\left(y_{i,2}=1|\,\mathbf{w}_i\right)=\Phi\left(\mathbf{w}_i\boldsymbol{\psi}\right), \tag{10}$$

where Φ is the cumulative distribution function (CDF) of the standard normal distribution, $y_{i,2}$ is a binary variable that indicates whether the ith respondent's prediction is greater ($y_{i,2}=1$) or lower ($y_{i,2}=0$) than professional forecasters' mean prediction in the second interview. Moreover, $\mathbf{w}_i$ is the vector of covariates (whose first entry is one), $\boldsymbol{\psi}$ is the vector of parameters. The main objective of estimating (10) is to understand whether households' potential overprediction (or underprediction) with respect to the SPF mean forecast in the first round interview affects the probability of overpredicting (or underpredicting) in the second interview.[30] To this end, we include $y_{i,1}$ in $\mathbf{w}_i$. We are also interested in understanding whether news absorption exerts any asymmetric impact depending on whether consumers have overpredicted or underpredicted in the first interview. Thus, along with $NEWS_i^P$, we also include the interaction term $NEWS_i^P \times y_{i,1}$ in $\mathbf{w}_i$.

Insert Tables 9 and 10 here

Tables 9 and 10 show that overprediction is inertial, as $y_{i,1}$ exerts a positive marginal effect on the probability that $y_{i,2}=1$. Also $NEWS_i^P$ has a positive effect, while the interaction term $NEWS_i^P \times y_{i,1}$ has no statistically meaningful impact on the probability of overpredicting, unless it appears as the only regressor in $\mathbf{w}_i$, together with $y_{i,1}$ and the vector of control variables.[31] The general tone of the news that consumers have perceived seems to have an asymmetric effect, as unfavorable news increase the chances of overpredicting, while favorable news have a negative marginal effect. Finally, the actual rate of inflation exerts a positive impact on the chances that $y_{i,2}=1$, which signals a certain overreaction to marginal variations in the inflation outlook.

[30] Only for 13.7% of the consumers who update their forecast from the first interview we cannot reject the null hypothesis that they adopt the SPF mean forecast.

[31] Otherwise, $NEWS^N$ does not exert a statistically significant impact when also $NEWS_i^P$ appears in $\mathbf{w}_i$.

Such a pessimistic attitude may indeed play a role in preventing households from making an efficient use of the information they perceive and adjust their expectations towards the SPF mean forecast.

With this picture at hand, a last important question needs to be addressed: how can we explain the coexistence of an updating mechanism à la Carroll – which is generally supported by the analysis with aggregate data – with the fact that household-level data are not consistent with the epidemiological hypothesis? To rationalize these mutually contradicting phenomena, one could argue that even though about half of the respondents update their expectations in the 'wrong' direction, yet the magnitude of their adjustments implies that the 'aggregate revision' moves in the right direction.[32] To test this hypothesis we compute, for all respondents that update their forecasts in the second interview, the average distance between their expectations and the SPF mean forecast, both in the first and the second interview. The statistics show that the average prediction gap narrows down by about 33.5% from the first to the second survey response, implying that the aggregate revision is on average dominated by the adjustment of those who update correctly, as compared with those that shift their projections further away from the SPF mean forecast.[33] The main implication of this result is that the empirical relevance of the model behind Equation (1) may actually result as a simple statistical artifact. In fact, the driving force of the expectation updating mechanism underlying consumers' mean forecast is represented by the size of the adjustment in household-level expectations, rather than by the epidemiological mechanism à la Carroll.

5 Concluding Remarks

This paper has extensively tested the epidemiological foundations of the sticky information model. We provide at best weak support to the view according to which consumers update their forecasts from the media, which are assumed to transmit professional forecasters' projections. An average of about 75% of the survey respondents revise their inflation forecasts with respect to their first interview, which has occurred six months before the second one. However, in

[32] Another possible explanation relies on the role of the predictions of those who are interviewed for the first time. In fact, it may be the case that even if incumbents' expectation updating does not work as predicted by Carroll, new respondents' predictions influence the dynamics of the overall average forecast. However, we test this hypothesis and find no statistical evidence that supports it.

[33] This mechanism turns out to be reinforced if these statistics include those respondents who do not update their predictions between the first and second interview. This is because the SPF mean forecast slightly decreases over time, driving down the average prediction gap from the first to the second interview.

each quarter only 5.8% of the households display some receptiveness to news on prices. Thus, we observe a fundamental disconnection between news on inflation and consumers' expectation updating. In fact, just a small fraction of those consumers who update their forecasts (13.7%) seem to revise expectation in accordance with the epidemiological model.

A key result is that hearing news on prices does not necessarily help at producing better forecasts, though it increases the probability that consumers revise their expectations. Consumers' expectation updating is also characterized by a marked degree of pessimism, which shows at different stages of the analysis. Importantly, the rate of CPI inflation and households' receptiveness to unfavorable news on prices exert a positive effect on the expectation gap between households' and professional forecasters' expectations. These factors also increase the likelihood that households persistently produce higher forecasts than professional forecasters mean expectation. Along with households' pessimistic attitude two alternative interpretations may be put forward to explain why consumers display stronger perception of unfavorable rather than favorable news on prices, and why these news exert a negative impact on the accuracy of their forecasts. On the one hand, news coverage may be biased by the views of players in the media, so that the views of professional forecasters are not reported objectively. On the other hand, as discussed by a number of contributors, professional forecasters often produce biased projections and, even if their views are objectively transmitted by the media, they may induce further distortions in consumers' forecasts. These considerations altogether emphasize the role of the epidemiological model of expectation formation as a transmission channel of potentially biased forecasts. In addition, the existence of a substantial fraction of consumers who do not adjust their forecasts towards professional forecasters' mean expectation is likely to induce an omitted-variable bias in Carroll's estimates of the absorption rate.

Our study has some relevant implications for evaluating the cost of disinflations and the role of communication and credibility in monetary policy. As to the first aspect, a number of authors stress the importance of quantifying the cost of disinflations in contexts where expectations are updated in a staggered fashion (e.g., Mankiw and Reis, 2001, 2002; Carroll, 2003, 2006). Time-varying measures of the frequency of expectation updating as the one we retrieve from household-level data can be used to explore these issues. In fact, in agreement with the rational inattention argument that consumers should be more intensely focused on news on inflation and inflation-fighting policies during periods of high inflation, we show that consumers' frequency of expectation updating has actually reached its maximum right before Volcker's disinflationary policy kicked in during the 1980s. As to the role of communication in policy making, Carroll suggests that credibility among experts may not be sufficient to achieve a desired inflationary outcome and suggests that the views of the experts need to be communicated effectively to the population to become effective. These may certainly be important aspects, provided that experts produce efficient forecasts and these are objectively reported in the media. Nevertheless, we should also account for the possibility that consumers do not necessarily follow experts' views or they may not make an efficient use of the information they retrieve from the media.

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Figures and Tables

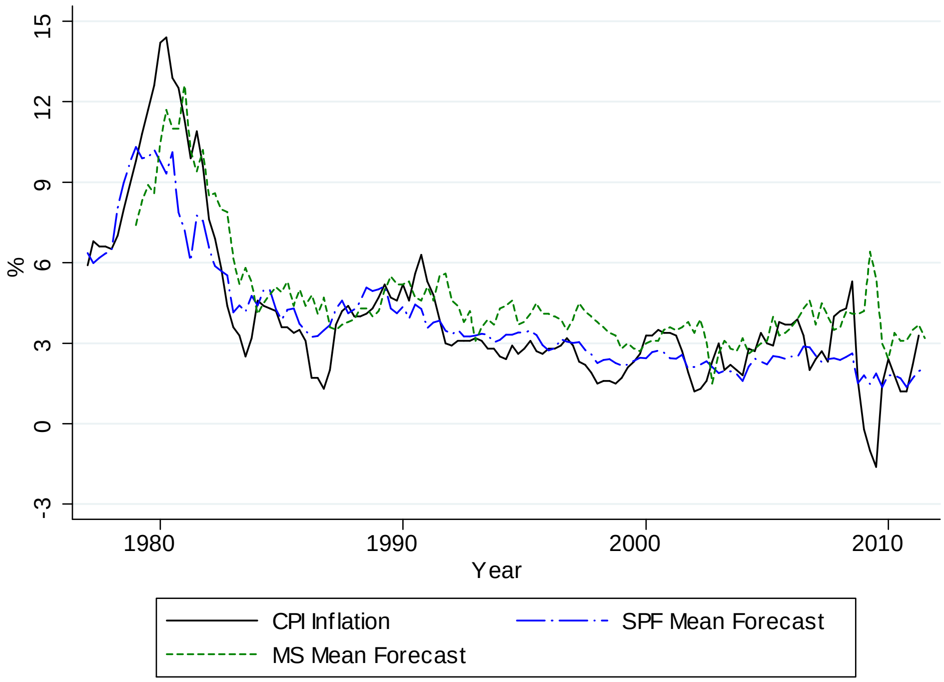

Figure 1: CPI Inflation, MS and SPF Mean Forecasts.

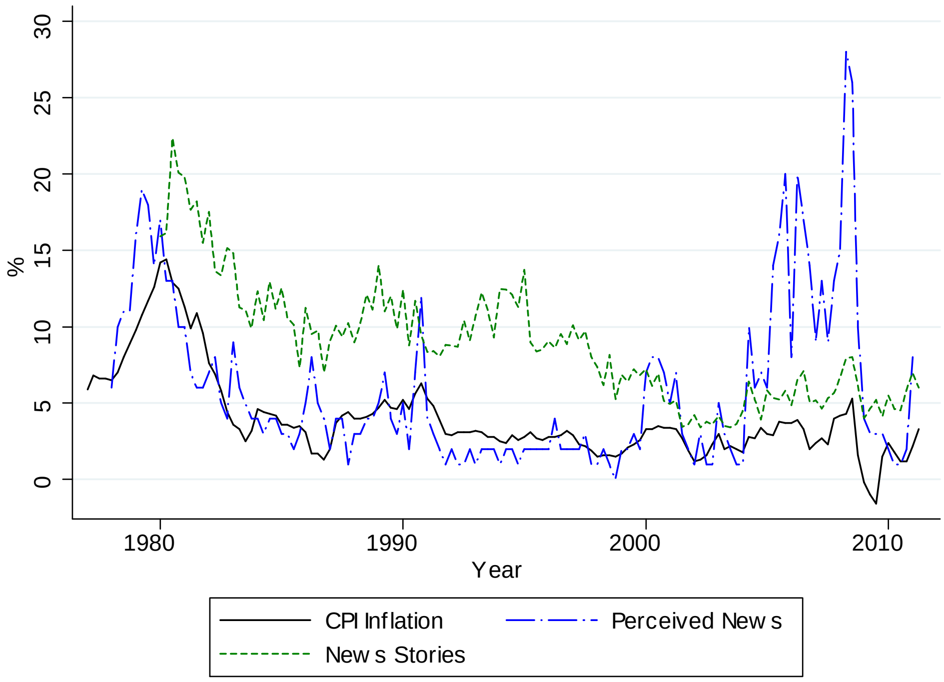

Figure 2: Perceived News and News Stories.

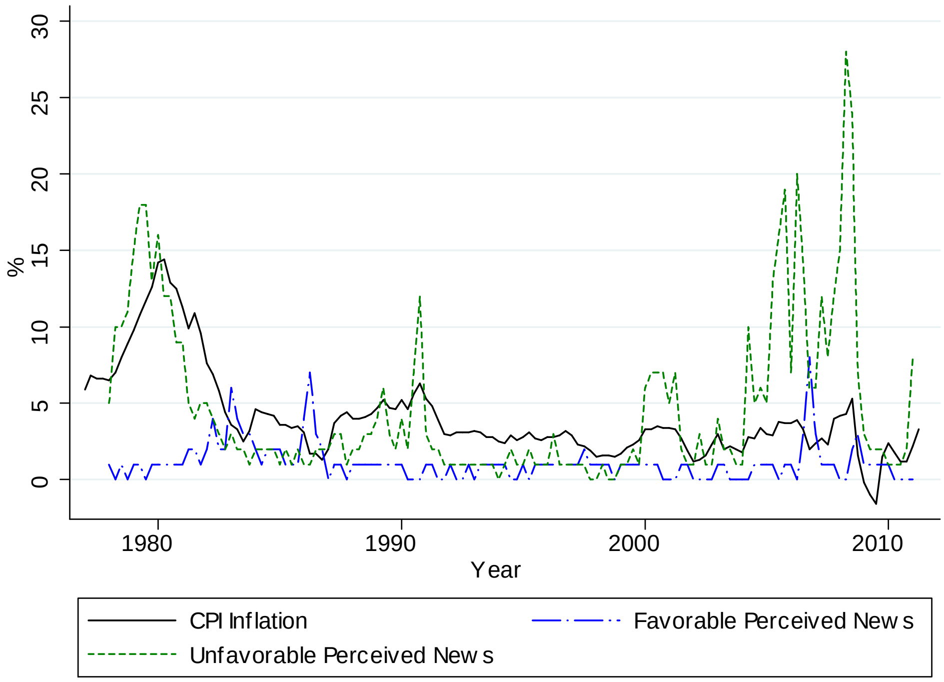

Figure 3: Favorable and Unfavorable Perceived News on Prices.

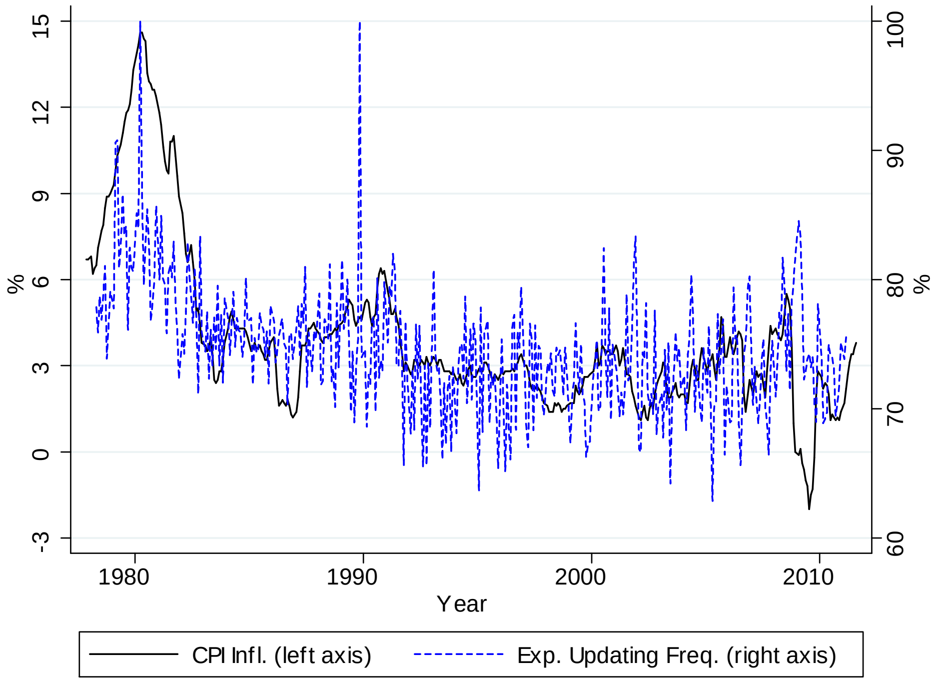

Figure 4: Time-Varying Frequency of Expectation Updating.

Table 1: Estimation of $\pi^C_{t+4|t} = \alpha_0 + \alpha_1 \pi^F_{t+4|t} + \alpha_2 \pi^C_{t+3|t-1} + \alpha_3 \pi_{t-1} + v_t$.

	Equations				
	1	2	3	4	5
α_0		0.245		0.373*	
		(0.177)		(0.218)	
α_1	0.280***	0.279***	0.278***	0.285***	
	(0.069)	(0.067)	(0.069)	(0.065)	
α_2	0.769***	0.726***	0.784***	0.642***	1.018***
	(0.059)	(0.069)	(0.061)	(0.091)	(0.040)
α_3			-0.015	0.059	-0.036
			(0.042)	(0.049)	(0.050)
Test	$\alpha_1 + \alpha_2 = 1$	$\alpha_0 = 0$	$\alpha_1 + \alpha_2 + \alpha_3 = 1$		$\alpha_2 + \alpha_3 = 1$
p-value	0.006	0.169	0.012		0.328
T	130	130	130	130	130
R^2	0.985	0.911	0.985	0.912	0.982

Notes: $\pi^C_{t+4|t}$ and $\pi^F_{t+4|t}$ are the (four quarters-ahead) mean expectations from the Michigan Survey and the Survey of Professional Forecasters in period t, respectively; π_{t-1} is the most recently published annual inflation rate as of time t. Robust standard errors computed with the Huber-White sandwich estimator are reported in parentheses. ***/**/* indicates significance at the 1/5/10% level.

Table 2: Estimation of $GAP_t = \gamma_0 + \gamma_1 NEWS_t^N + \gamma_2 NEWS_t^P + \gamma_3 \left(NEWS_t^P \times NEWS_t^N \right) + \mu_t$.

	Equations							
	$GAPSQ_t$	$GAPSQ_t^*$	$GAPSQ_t$	$GAPSQ_t^*$	$GAPSQ_t$	$GAPSQ_t^*$	$GAPSQ_t$	$GAPSQ_t^*$
γ_0	0.027	2.510**	-0.294	-1.034	-2.153**	-1.079	2.091	-3.632**
	(0.864)	(1.119)	(0.437)	(1.267)	(1.062)	(1.308)	(1.537)	(1.772)
γ_1	0.236**	0.046			0.192*	-0.018	-0.330	0.294*
	(0.115)	(0.076)			(0.098)	(0.124)	(0.209)	(0.149)
γ_2			0.435***	0.727**	0.481***	0.773**	-0.112	1.126**
			(0.110)	(0.282)	(0.119)	(0.334)	(0.307)	(0.453)
γ_3							0.073*	-0.043
							(0.042)	(0.027)
T	123	122	131	130	123	122	123	122
R^2	0.057	0.001	0.364	0.320	0.455	0.323	0.561	0.335

Notes: GAP_t=$\{GAPSQ_t$,$GAPSQ_t^*\}$, where $GAPSQ_t$ is the squared difference between the MS and SPF mean inflation forecasts and $GAPSQ_t^*$ is the squared difference between the MS mean inflation forecast and CPI inflation (at the forecast horizon); $NEWS_t^P$ is the fraction of MS participants that have heard of favorable or unfavorable changes prices in the period before the interview; $NEWS_t^N$ is an index of the intensity of news coverage of inflation in the New York Times and the Washington Post. Robust standard errors computed with the Huber-White sandwich estimator are reported in parentheses. ***/**/* indicates significance at the 1/5/10% level.

Table 3: Favorable and Unfavorable News, Expectation Updating and Forecast Accuracy.

Table 3(a)		Table 3(b)						
	$\pi^C_{t+4\|t}$		$GAPSQ_t$	$GAPSQ^*_t$	$GAPSQ_t$	$GAPSQ^*_t$	$GAPSQ_t$	$GAPSQ^*_t$
α_1^U	0.290***	γ_0	2.503***	3.680***	0.107	-0.352	0.191	-0.222
	(0.082)		(0.446)	(0.851)	(0.332)	(0.975)	(0.311)	(1.052)
α_1^F	0.284***	γ_1^F	-0.230	-0.392			-0.069	-0.106
	(0.068)		(0.153)	(0.385)			(0.101)	(0.297)
α_2^U	0.775***	γ_1^U			0.454***	0.758***	0.453***	0.756***
	(0.070)				(0.112)	(0.285)	(0.112)	(0.286)
α_2^F	0.714***							
	(0.061)							
T	130	T	131	130	131	130	131	130
R^2	0.986	R^2	0.005	0.005	0.391	0.343	0.392	0.344

Notes: Table 3(a) reports the OLS estimates of Equation (4); Table 3(b) reports the OLS estimates from Equation (5). Robust standard errors computed with the Huber-White sandwich estimator are reported in parentheses. ***/**/* indicates significance at the 1/5/10% level.

Table 4: Predictive Accuracy, Expectation Updating and News Perception.

	AFE	AFE Conditional on News	
		YES	NO
Updated Forecast	3.09	3.33	3.10
Forecast Stays the Same	2.76	2.99	2.77

Notes: Table 4 reports the average forecast error (AFE) implied by household-level data: this is computed both for agents that have updated their forecast with respect to the first interview (first row, labelled 'Updated Forecast') and those that have not revised their forecasts (second row, labelled 'Forecast Stays the Same'). Moreover, we compute the average forecast error for those who have heard of recent changes in prices (column labelled "AFE Conditional on News-YES") and those who have not (column labelled "AFE Conditional on News-NO").

Table 5: Determinants of Expectation Updating at the Household-Level.

	Models				
	Model 1	Model 2	Model 3	Model 4	Model 5
$NEWS_i^P$	0.042***		0.031***	0.035***	0.034***
	(0.008)		(0.008)	(0.008)	(0.008)
$NEWS^N$		0.004***			-0.001
		(0.0004)			(0.001)
π			0.007***	0.005***	0.005***
			(0.001)	(0.001)	(0.001)
π^F				0.007***	0.009***
				(0.002)	(0.003)
$Controls$	yes	yes	yes	yes	yes
SSC	0.000***	0.001***	0.005***	0.050*	0.000***
N	72,853	71,644	72,853	71,880	70,770
$Wald\ Test\ (\chi^2)$	204***	260***	346***	353***	333***

Notes: Table 5 reports the marginal partial effects from the estimation of $\Pr(z_i = 1|\mathbf{h}_i) = \Phi(\mathbf{h}_i\boldsymbol{\xi})$, where $\Phi(\cdot)$ is the CDF of the standard normal distribution, $\mathbf{h}_i$ is the vector of covariates and $\boldsymbol{\xi}$ is a vector of coefficients; z_i, takes value one if the i^{th} respondent has updated her expectations from the first interview and zero otherwise. The vector $\mathbf{h}_i$ includes: $NEWS_i^P$, which is an individual-specific indicator of news perception (this equals one if the interviewee has heard of changes in prices in the last few months before the interview and zero otherwise); $NEWS^N$, that is an index of the intensity of news coverage of inflation in the New York Times and the Washington Post; π, which denotes the last observed CPI inflation rate; π^F, the mean forecast from the the Survey of Professional Forecasters at the time the individual is interviewed; a vector $\mathbf{x}_i$ of control variables, where we include information on the socio-demographic characteristics of the MS respondents (such as gender, age, income, education, race, marital status, location in the US), as well as a number of interaction terms among them. To account for the presence of question attrition, we perform a sample selection correction test: SSC stands for the p-value of the Wald test of independence from the sample selection equation (which includes as regressors some socio-demographic characteristics as well as the tone of the news consumers have heard). A constant has been included in all regressions. Standard errors are calculated with the delta method (Oehlert, 1992) and are reported in parentheses. ***/**/* indicates significance at the 1/5/10% level.

Table 6: Determinants of Expectation Updating at the Household-Level.

	Models				
	Model 1	Model 2	Model 3	Model 4	Model 5
$NEWS_i^P$	0.033***		0.027***	0.029***	0.030***
	(0.006)		(0.007)	(0.001)	(0.007)
$NEWS^N$		0.003***			-0.001
		(0.001)			(0.001)
π			0.006***	0.004***	0.004***
			(0.001)	(0.001)	(0.001)
π^F				0.005***	0.007***
				(0.002)	(0.003)
$Controls$	yes	yes	yes	yes	yes
SSC	0.000***	0.000***	0.269	0.255	0.352
N	105,607	104,497	105,607	104,634	103,524
$Wald\ Test\ (\chi^2)$	825***	466***	435***	445***	456***

Notes: Table 6 reports the marginal partial effects from the estimation of $\Pr(z_i = 1|\, \mathbf{h}_i) = \Phi(\mathbf{h}_i \boldsymbol{\xi})$, where $\Phi(\cdot)$ is the CDF of the standard normal distribution, $\mathbf{h}_i$ is the vector of covariates and $\boldsymbol{\xi}$ is a vector of coefficients; z_i, takes value one if the i^{th} respondent has updated her expectations from the first interview and zero otherwise. The vector $\mathbf{h}_i$ includes: $NEWS_i^P$, which is an individual-specific indicator of news perception (this equals one if the interviewee has heard of changes in prices in the last few months before the interview and zero otherwise); $NEWS^N$, that is an index of the intensity of news coverage of inflation in the New York Times and the Washington Post; π, which denotes the last observed CPI inflation rate; π^F, the mean forecast from the the Survey of Professional Forecasters at the time the individual is interviewed; a vector $\mathbf{x}_i$ of control variables, where we include information on the socio-demographic characteristics of the MS respondents (such as gender, age, income, education, race, marital status, location in the US), as well as a number of interaction terms among them. To account for the presence of interview attrition, we perform a sample selection correction test: SSC stands for the p-value of the Wald test of independence from the sample selection equation (which includes as regressors some socio-demographic characteristics as well as the tone of the news consumers have heard). A constant has been included in all regressions. Standard errors are calculated with the delta method (Oehlert, 1992) and are reported in parentheses. $^{***}/^{**}/^{*}$ indicates significance at the 1/5/10% level.

Table 7: 'GAP' Linear Regressions (Random Effects).

	Equations $GAPSQ_{i,t}$	$GAPSQ_{i,t}$	$GAPSQ_{i,t}$	$GAPSQ_{i,t}$	$GAPSQ_{i,t}$
$Constant$	31.125***	11.720***	12.817***	10.305***	16.693***
	(1.483)	(1.573)	(1.555)	(1.595)	(1.557)
$NEWS_{i,t}^{P}$	8.454***		7.285***	8.297***	
	(0.691)		(0.694)	(0.728)	
$NEWS_{t}^{N}$		1.298***		0.948***	
		(0.068)		(0.068)	
$\pi_{t+12\|t}^{F}$			3.319***	1.213***	-0.234
			(0.095)	(0.212)	(0.156)
π_{t-1}					2.363***
					(0.086)
$NEWS_{i,t}^{P,U}$					5.489***
					(0.716)
$NEWS_{i,t}^{P,F}$					-1.852
					(1.597)
$Controls$	yes	yes	yes	yes	yes
$N \times T$	172,838	168,391	172,838	168,391	172,838
$Wald\ Test\ (\chi^2)$	3,388***	4,221***	4,654***	4,360***	5,331***

Notes: We estimate (8) by feasible GLS. $GAPSQ_{i,t}$ is the squared difference between the MS household-specific forecast and the SPF mean inflation forecast; $NEWS_{i,t}^{P}$ is an individual-specific indicator of news perception (which equals one if the interviewee has heard of changes in prices in the last few months and zero otherwise); $NEWS_{i,t}^{P,F}$ and $NEWS_{i,t}^{P,U}$ are individual-specific responses about the content of the news the survey participant has heard about; $NEWS_{t}^{N}$ is an index of the intensity of news coverage of inflation in the New York Times and the Washington Post; π_{t-1} denotes the last observed CPI inflation rate as of time t; $\pi_{t+12|t}^{F}$ is the (twelve months-ahaed) mean forecast from the Survey of Professional Forecasters; the vector of control variables includes information on the socio-demographic characteristics of the ith respondent (such as gender, age, income, education, race, marital status, location in the US), as well as some interaction terms among these characteristics. Clustered standard errors (computed at the individual level through the sandwich estimator) are reported in parentheses. ***/**/* indicates significance at the 1/5/10% level.

Table 8: 'GAP' Linear Regressions (Random Effects).

	Equations $GAPSQ^{*}_{i,t}$	$GAPSQ^{*}_{i,t}$	$GAPSQ^{*}_{i,t}$	$GAPSQ^{*}_{i,t}$	$GAPSQ^{*}_{i,t}$
$Constant$	32.017***	10.342***	10.646***	11.658***	15.498***
	(1.580)	(1.659)	(1.656)	(1.680)	(1.659)
$NEWS^{P}_{i,t}$	10.923***		9.553***	10.499***	
	(0.734)		(0.742)	(0.781)	
$NEWS^{N}_{t}$		1.429***		1.684***	
		(0.035)		(0.073)	
$\pi^{F}_{t+12\|t}$			3.874***	-0.966***	-0.556***
			(0.097)	(0.225)	(0.170)
π_{t-1}					2.943***
					(0.086)
$NEWS^{P,U}_{i,t}$					7.343***
					(0.762)
$NEWS^{P,F}_{i,t}$					-2.790*
					(1.621)
$Controls$	yes	yes	yes	yes	yes
$N \times T$	172,838	168,391	172,838	168,391	172,838
$Wald\ Test\ (\chi^2)$	3,480***	4,496***	5,341***	4,647***	7,023***

Notes: We estimate (8) by feasible GLS. $GAPSQ^{*}_{i,t}$ is the squared difference between the MS household-specific forecast and CPI inflation (at the forecast horizon); $NEWS^{P}_{i,t}$ is an individual-specific indicator of news perception (which equals one if the interviewee has heard of changes in prices in the last few months and zero otherwise); $NEWS^{P,F}_{i,t}$ and $NEWS^{P,U}_{i,t}$ are individual-specific responses about the content of the news the survey participant has heard about; $NEWS^{N}_{t}$ is an index of the intensity of news coverage of inflation in the New York Times and the Washington Post; π_{t-1} denotes the last observed CPI inflation rate as of time t; $\pi^{F}_{t+12|t}$ is the (twelve months-ahaed) mean forecast from the Survey of Professional Forecasters; the vector of control variables includes information on the socio-demographic characteristics of the ith respondent (such as gender, age, income, education, race, marital status, location in the US), as well as some interaction terms among these characteristics. Clustered standard errors (computed at the individual level through the sandwich estimator) are reported in parentheses. ***/**/* indicates significance at the 1/5/10% level.

Table 9: Determinants of the Forecast Bias at the Household-Level.

	Models Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
$y_{i,1}$	0.279***	0.263***	0.264***	0.258***	0.265***	0.272***	0.277***
	(0.005)	(0.003)	(0.005)	(0.006)	(0.005)	(0.004)	(0.005)
π	0.002***	0.022***	0.035***	0.034***	0.035***		
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)		
π^F			-0.081***	-0.078***	-0.081***		
			(0.003)	(0.003)	(0.003)		
$NEWS_i^P$	0.134***		0.109***		0.115***		0.139***
	(0.009)		(0.009)		(0.013)		(0.013)
$NEWS^N$		-0.019***					
		(0.001)					
$NEWS_i^{P,U}$				0.112***			
				(0.009)			
$NEWS_i^{P,F}$				-0.088**			
				(0.041)			
$NEWS_i^P \times y_{i,1}$					-0.011	0.119***	-0.003
					(0.018)	(0.013)	(0.018)
$Controls$	yes	yes	yes	yes	yes	yes	yes
SSC	0.006***	0.000***	0.074*	0.038**	0.078*	0.000***	0.002***
N	68,216	67,106	67,243	71,880	67,243	68,216	68,216
$Wald\ Test\ (\chi^2)$	5,374***	6,992***	6,579***	5,203***	6,630***	4,936***	5,487***

Notes: Table 9 reports the marginal partial effects from the estimation of $\Pr(y_{i,2} = 1|\mathbf{w}_i) = \Phi(\mathbf{w}_i\boldsymbol{\psi})$, where $\Phi(\cdot)$ is the CDF of the standard normal distribution, $\mathbf{w}_i$ is the vector of covariates and $\boldsymbol{\psi}$ is a vector of coefficients; $y_{i,2}$ is a binary variable that indicates whether the ith respondent's prediction is greater ($y_{i,2}$= 1) or lower ($y_{i,2}$= 0) than professional forecasters' mean prediction in the second interview. The vector $\mathbf{w}_i$ includes: the binary variable $y_{i,1}$, which indicates whether the ith respondent's prediction has been greater ($y_{i,1}$= 1) or lower ($y_{i,1}$= 0) than professional forecasters' mean prediction in the first interview; $NEWS_i^P$, which is an individual-specific indicator of news perception (which equals one if the interviewee has heard of changes in prices in the last few months before the interview and zero otherwise); $NEWS^N$ is an index of the intensity of news coverage of inflation in the New York Times and the Washington Post; $NEWS_{i,t}^{P,F}$ and $NEWS_{i,t}^{P,U}$ are individual-specific responses about the content of the news the survey participant has heard about; π, which denotes the last observed CPI inflation rate; π^F, which denotes the (twelve months-ahaed) mean forecast from the Survey of Professional Forecasters; a vector $\mathbf{x}_i$ of control variables, where we include information on the socio-demographic characteristics (such as gender, age, income, education, race, marital status, location in the US), as well as a number of interaction terms among them. re we include information on the socio-demographic characteristics of the MS respondents (such as gender, age, income, education, race, marital status, location in the US), as well as a number of interaction terms among them. To account for the presence of question attrition, we perform a sample selection correction test: SSC stands for the p-value of the Wald test of independence from the sample selection equation (which includes as regressors some socio-demographic characteristics as well as the tone of the news consumers have heard). A constant has been included in all regressions. Standard errors are calculated with the delta method (Oehlert, 1992) and are reported in parentheses. ***/**/* indicates significance at the 1/5/10% level.

Table 10: Determinants of the Forecast Bias at the Household-Level.

	Models Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
$y_{i,1}$	0.248*** (0.015)	0.199*** (0.005)	0.220*** (0.011)	0.231*** (0.016)	0.227*** (0.016)	0.214*** (0.007)	0.244*** (0.016)
π	0.002*** (0.001)	0.017*** (0.001)	0.029*** (0.002)	0.030*** (0.002)	0.030*** (0.002)		
π^F			-0.067*** (0.004)	-0.070*** (0.005)	-0.069*** (0.005)		
$NEWS_i^P$	0.115*** (0.011)		0.084*** (0.010)		0.098*** (0.013)		0.120*** (0.013)
$NEWS^N$		-0.014*** (0.001)					
$NEWS_i^{P,U}$				0.112*** (0.009)			
$NEWS_i^{P,F}$				-0.088** (0.041)			
$NEWS_i^P \times y_{i,1}$					-0.012 (0.011)	0.080*** (0.011)	-0.008 (0.015)
$Controls$	yes	yes	yes	yes	yes	yes	yes
SSC	0.000***	0.000***	0.000***	0.001***	0.001***	0.000***	0.000***
N	68,216	67,106	67,243	67,243	67,243	68,216	68,216
$Wald\ Test\ (\chi^2)$	4,620***	4,929***	4,510***	4,792***	4,672***	4,433***	4,487***

Notes: Table 10 reports the marginal partial effects from the estimation of $\Pr(y_{i,2} = 1|\mathbf{w}_i) = \Phi(\mathbf{w}_i\boldsymbol{\psi})$, where $\Phi(\cdot)$ is the CDF of the standard normal distribution, $\mathbf{w}_i$ is the vector of covariates and $\boldsymbol{\psi}$ is a vector of coefficients; $y_{i,2}$ is a binary variable that indicates whether the ith respondent's prediction is greater ($y_{i,2}= 1$) or lower ($y_{i,2}= 0$) than professional forecasters' mean prediction in the second interview. The vector $\mathbf{w}_i$ includes: the binary variable $y_{i,1}$, which indicates whether the ith respondent's prediction has been greater ($y_{i,1}= 1$) or lower ($y_{i,1}= 0$) than professional forecasters' mean prediction in the first interview; $NEWS_i^P$, which is an individual-specific indicator of news perception (which equals one if the interviewee has heard of changes in prices in the last few months before the interview and zero otherwise); $NEWS^N$ is an index of the intensity of news coverage of inflation in the New York Times and the Washington Post; $NEWS_{i,t}^{P,F}$ and $NEWS_{i,t}^{P,U}$ are individual-specific responses about the content of the news the survey participant has heard about; π, which denotes the last observed CPI inflation rate; π^F, which denotes the (twelve months-ahaed) mean forecast from the Survey of Professional Forecasters; a vector $\mathbf{x}_i$ of control variables, where we include information on the socio-demographic characteristics (such as gender, age, income, education, race, marital status, location in the US), as well as a number of interaction terms among them. To account for the presence of interview attrition, we perform a sample selection correction test: SSC stands for the p-value of the Wald test of independence from the sample selection equation (which includes as regressors some socio-demographic characteristics as well as the tone of the news consumers have heard). A constant has been included in all regressions. Standard errors are calculated with the delta method (Oehlert, 1992) and are reported in parentheses. ***/**/* indicates significance at the 1/5/10% level.

Appendix A: Analysis on the 1984-2004 Sample

Table A1: Estimation of $\pi^C_{t+4|t} = \alpha_0 + \alpha_1 \pi^F_{t+4|t} + \alpha_2 \pi^C_{t+3|t-1} + \alpha_3 \pi_{t-1} + v_t$.

	Equations 1	2	3	4	5
α_0		0.780***		0.885***	
		(0.246)		(0.258)	
α_1	0.261***	0.240***	0.263***	0.244***	
	(0.058)	(0.057)	(0.059)	(0.058)	
α_2	0.780***	0.608***	0.754***	0.495***	0.980***
	(0.050)	(0.068)	(0.073)	(0.099)	(0.058)
α_3			0.030	0.104	0.012
			(0.066)	(0.067)	(0.074)
Test	$\alpha_1 + \alpha_2 = 1$	$\alpha_0 = 0$	$\alpha_1 + \alpha_2 + \alpha_3 = 1$		$\alpha_2 + \alpha_3 = 1$
p-value	0.009	0.002	0.042		0.714
T	94	94	94	94	94
R^2	0.986	0.669	0.986	0.676	0.984

Notes: $\pi^C_{t+4|t}$ and $\pi^F_{t+4|t}$ are the (four quarters-ahead) mean expectations from the Michigan Survey and the Survey of Professional Forecasters in period t, respectively; π_{t-1} is the most recently published annual inflation rate as of time t. Robust standard errors computed with the Huber-White sandwich estimator are reported in parentheses. ***/**/* indicates significance at the 1/5/10% level.

Table A2: Estimation of $GAP_t = \gamma_0 + \gamma_1 NEWS_t^N + \gamma_2 NEWS_t^P + \gamma_3 \left(NEWS_t^P \times NEWS_t^N\right) + \mu_t$.

	Equations							
	$GAPSQ_t$	$GAPSQ_t^*$	$GAPSQ_t$	$GAPSQ_t^*$	$GAPSQ_t$	$GAPSQ_t^*$	$GAPSQ_t$	$GAPSQ_t^*$
γ_0	1.247***	1.213**	0.431***	1.317***	0.398	0.681	0.025	-0.642
	(0.298)	(0.593)	(0.111)	(0.326)	(0.272)	(0.609)	(0.347)	(0.800)
γ_1	-0.022	0.055			0.004	0.071	0.056	0.257**
	(0.031)	(0.062)			(0.030)	(0.062)	(0.051)	(0.106)
γ_2			0.154***	0.089	0.154***	0.097	0.245**	0.418**
			(0.027)	(0.066)	(0.028)	(0.066)	(0.093)	(0.186)
γ_3							-0.013	-0.047*
							(0.015)	(0.026)
T	94	94	94	94	94	94	94	94
R^2	0.005	0.005	0.359	0.023	0.360	0.032	0.372	0.063

Notes: GAP_t=$\{GAPSQ_t$,$GAPSQ_t^*\}$, where $GAPSQ_t$ is the squared difference between the MS and SPF mean inflation forecasts and $GAPSQ_t^*$ is the squared difference between the MS mean inflation forecast and CPI inflation (at the forecast horizon); $NEWS_t^P$ is the fraction of MS participants that have heard of favorable or unfavorable changes prices in the period before the interview; $NEWS_t^N$ is an index of the intensity of news coverage of inflation in the New York Times and the Washington Post. Robust standard errors computed with the Huber-White sandwich estimator are reported in parentheses. ***/**/* indicates significance at the 1/5/10% level.

Table A3: Favorable and Unfavorable News, Expectation Updating and Forecast Accuracy.

Table A3(a)		Table A3(b)						
	$\pi^C_{t+4\|t}$		$GAPSQ_t$	$GAPSQ^*_t$	$GAPSQ_t$	$GAPSQ^*_t$	$GAPSQ_t$	$GAPSQ^*_t$
α_1^U	0.254***	γ_0	1.278***	1.904***	0.529***	1.346***	0.678***	1.540***
	(0.093)		(0.145)	(0.279)	(0.092)	(0.278)	(0.106)	(0.329)
α_1^F	0.304***	γ_1^F	-0.216***	-0.219**			-0.127**	-0.165
	(0.065)		(0.071)	(0.103)			(0.048)	(0.100)
α_2^U	0.816***	γ_1^U			0.174***	0.110*	0.167***	0.101
	(0.078)				(0.026)	(0.066)	(0.026)	(0.067)
α_2^F	0.700***							
	(0.060)							
T	94	T	94	94	94	94	94	94
R^2	0.988	R^2	0.068	0.014	0.460	0.035	0.483	0.043

Notes: Table A3(a) reports the OLS estimates of Equation (4); Table A3(b) reports the OLS estimates from Equation (5). Robust standard errors computed with the Huber-White sandwich estimator are reported in parentheses. ***/**/* indicates significance at the 1/5/10% level.

Table A4: Determinants of Expectation Updating at the Household-Level.

	Models Model 1	Model 2	Model 3	Model 4	Model 5
$NEWS_i^P$	0.044***		0.040***	0.042***	0.041***
	(0.013)		(0.013)	(0.013)	(0.007)
$NEWS^N$		0.002**			-0.002
		(0.001)			(0.001)
π			0.007***	0.003	0.004**
			(0.002)	(0.002)	(0.002)
π^F				0.009***	0.012***
				(0.003)	(0.003)
$Controls$	yes	yes	yes	yes	yes
SSC	0.561	0.343	0.676	0.586	0.624
N	47,940	47,940	47,940	47,940	47,940
$Wald\ Test$ (χ^2)	131***	134***	150***	162***	164***

Notes: Table A4 reports the marginal partial effects from the estimation of $\Pr(z_i = 1 | \mathbf{h}_i) = \Phi(\mathbf{h}_i \boldsymbol{\xi})$, where $\Phi(\cdot)$ is the CDF of the standard normal distribution, $\mathbf{h}_i$ is the vector of covariates and $\boldsymbol{\xi}$ is a vector of coefficients; z_i, takes value one if the ith respondent has updated her expectations from the first interview and zero otherwise. The vector $\mathbf{h}_i$ includes: $NEWS_i^P$, which is an individual-specific indicator of news perception (this equals one if the interviewee has heard of changes in prices in the last few months before the interview and zero otherwise); $NEWS^N$, that is an index of the intensity of news coverage of inflation in the New York Times and the Washington Post; π, which denotes the last observed CPI inflation rate; π^F, the mean forecast from the the Survey of Professional Forecasters at the time the individual is interviewed; a vector $\mathbf{x}_i$ of control variables, where we include information on the socio-demographic characteristics of the MS respondents (such as gender, age, income, education, race, marital status, location in the US), as well as a number of interaction terms among them. To account for the presence of question attrition, we perform a sample selection correction test: SSC stands for the p-value of the Wald test of independence from the sample selection equation (which includes as regressors some socio-demographic characteristics as well as the tone of the news consumers have heard). A constant has been included in all regressions. Standard errors are calculated with the delta method (Oehlert, 1992) and are reported in parentheses. ***/**/* indicates significance at the 1/5/10% level.

Table A5: Determinants of Expectation Updating at the Household-Level.

	Models				
	Model 1	Model 2	Model 3	Model 4	Model 5
$NEWS_i^P$	0.033***		0.031***	0.032***	0.031***
	(0.010)		(0.010)	(0.010)	(0.010)
$NEWS^N$		0.001**			-0.001
		(0.001)			(0.001)
π			0.005***	0.003*	0.003**
			(0.001)	(0.002)	(0.002)
π^F				0.007***	0.009***
				(0.002)	(0.002)
$Controls$	yes	yes	yes	yes	yes
SSC	0.000***	0.000***	0.005***	0.002***	0.001***
N	67,723	67,723	67,723	67,723	67,723
$Wald\ Test\ (\chi^2)$	606***	612***	606***	618***	620***

Notes: Table A5 reports the marginal partial effects from the estimation of $\Pr(z_i = 1 | \mathbf{h}_i) = \Phi(\mathbf{h}_i\boldsymbol{\xi})$, where $\Phi(\cdot)$ is the CDF of the standard normal distribution, $\mathbf{h}_i$ is the vector of covariates and $\boldsymbol{\xi}$ is a vector of coefficients; z_i, takes value one if the ith respondent has updated her expectations from the first interview and zero otherwise. The vector $\mathbf{h}_i$ includes: $NEWS_i^P$, which is an individual-specific indicator of news perception (this equals one if the interviewee has heard of changes in prices in the last few months before the interview and zero otherwise); $NEWS^N$, that is an index of the intensity of news coverage of inflation in the New York Times and the Washington Post; π, which denotes the last observed CPI inflation rate; π^F, the mean forecast from the the Survey of Professional Forecasters at the time the individual is interviewed; a vector $\mathbf{x}_i$ of control variables, where we include information on the socio-demographic characteristics of the MS respondents (such as gender, age, income, education, race, marital status, location in the US), as well as a number of interaction terms among them. To account for the presence of interview attrition, we perform a sample selection correction test: SSC stands for the p-value of the Wald test of independence from the sample selection equation (which includes as regressors some socio-demographic characteristics as well as the tone of the news consumers have heard). A constant has been included in all regressions. Standard errors are calculated with the delta method (Oehlert, 1992) and are reported in parentheses. ***/**/* indicates significance at the 1/5/10% level.

Table A6: 'GAP' Linear Regressions (Random Effects).

	Equations $GAPSQ_{i,t}$	$GAPSQ_{i,t}$	$GAPSQ_{i,t}$	$GAPSQ_{i,t}$	$GAPSQ_{i,t}$
$Constant$	23.648***	17.327***	15.380***	14.586***	13.235***
	(1.758)	(1.846)	(1.895)	(1.893)	(1.898)
$NEWS_{i,t}^{P}$	5.383***		5.299***	5.349***	
	(1.042)		(1.042)	(1.043)	
$NEWS_{t}^{N}$		0.582***		0.310***	
		(0.052)		(0.075)	
$\pi_{t+12\|t}^{F}$			2.046***	1.401***	0.911***
			(0.169)	(0.242)	(0.207)
π_{t-1}					1.805***
					(0.170)
$NEWS_{i,t}^{P,U}$					5.278***
					(1.130)
$NEWS_{i,t}^{P,F}$					-1.002
					(1.562)
$Controls$	yes	yes	yes	yes	yes
$N \times T$	113,036	113,036	113,036	113,036	113,036
$Wald\ Test\ (\chi^2)$	2,274***	2,275***	2,327***	2,329***	2,354***

Notes: We estimate (8) by feasible GLS. $GAPSQ_{i,t}$ is the squared difference between the MS household-specific forecast and the SPF mean inflation forecast; $NEWS_{i,t}^{P}$ is an individual-specific indicator of news perception (which equals one if the interviewee has heard of changes in prices in the last few months and zero otherwise); $NEWS_{i,t}^{P,F}$ and $NEWS_{i,t}^{P,U}$ are individual-specific responses about the content of the news the survey participant has heard about; $NEWS_{t}^{N}$ is an index of the intensity of news coverage of inflation in the New York Times and the Washington Post; π_{t-1} denotes the last observed CPI inflation rate as of time t; $\pi_{t+12|t}^{F}$ is the (twelve months-ahaed) mean forecast from the Survey of Professional Forecasters; the vector of control variables includes information on the socio-demographic characteristics of the ith respondent (such as gender, age, income, education, race, marital status, location in the US), as well as some interaction terms among these characteristics. Clustered standard errors (computed at the individual level through the sandwich estimator) are reported in parentheses. ***/**/* indicates significance at the 1/5/10% level.

Table A7: 'GAP' Linear Regressions (Random Effects).

	Equations $GAPSQ^{*}_{i,t}$	$GAPSQ^{*}_{i,t}$	$GAPSQ^{*}_{i,t}$	$GAPSQ^{*}_{i,t}$	$GAPSQ^{*}_{i,t}$
$Constant$	25.207***	18.292***	17.295***	16.193***	14.589***
	(1.877)	(1.963)	(2.013)	(2.010)	(2.013)
$NEWS^{P}_{i,t}$	5.705***		5.625***	5.694***	
	(1.091)		(1.091)	(1.091)	
$NEWS^{N}_{t}$		0.636***		0.431***	
		(0.054)		(0.077)	
$\pi^{F}_{t+12\|t}$			1.958***	1.061***	0.524**
			(0.175)	(0.252)	(0.215)
π_{t-1}					2.280***
					(0.177)
$NEWS^{P,U}_{i,t}$					5.578***
					(1.183)
$NEWS^{P,F}_{i,t}$					-2.083
					(1.599)
$Controls$	yes	yes	yes	yes	yes
$N \times T$	113,036	113,036	113,036	113,036	113,036
$Wald\ Test\ (\chi^2)$	2,207***	2,215***	2,253***	2,253***	2,315***

Notes: We estimate (8) by feasible GLS. $GAPSQ^{*}_{i,t}$ is the squared difference between the MS household-specific forecast and CPI inflation (at the forecast horizon); $NEWS^{P}_{i,t}$ is an individual-specific indicator of news perception (which equals one if the interviewee has heard of changes in prices in the last few months and zero otherwise); $NEWS^{P,F}_{i,t}$ and $NEWS^{P,U}_{i,t}$ are individual-specific responses about the content of the news the survey participant has heard about; $NEWS^{N}_{t}$ is an index of the intensity of news coverage of inflation in the New York Times and the Washington Post; π_{t-1} denotes the last observed CPI inflation rate as of time t; $\pi^{F}_{t+12|t}$ is the (twelve months-ahaed) mean forecast from the Survey of Professional Forecasters; the vector of control variables includes information on the socio-demographic characteristics of the ith respondent (such as gender, age, income, education, race, marital status, location in the US), as well as some interaction terms among these characteristics. Clustered standard errors (computed at the individual level through the sandwich estimator) are reported in parentheses. $^{***}/^{**}/^{*}$ indicates significance at the 1/5/10% level.

Table A8: Determinants of the Forecast Bias at the Household-Level.

	Models Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
$y_{i,1}$	0.265***	0.260***	0.251***	0.251***	0.250***	0.263***	0.265***
	(0.005)	(0.004)	(0.005)	(0.006)	(0.005)	(0.004)	(0.005)
π	-0.000	0.015***	0.032***	0.032***	0.032***		
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)		
π^F			-0.084***	-0.084***	-0.084***		
			(0.003)	(0.003)	(0.003)		
$NEWS_i^P$	0.079***		0.071***		0.069***		0.075***
	(0.013)		(0.013)		(0.019)		(0.019)
$NEWS^N$		-0.012***					
		(0.001)					
$NEWS_i^{P,U}$				0.089***			
				(0.014)			
$NEWS_i^{P,F}$				-0.066			
				(0.042)			
$NEWS_i^P \times y_{i,1}$					0.004	0.081***	0.008
					(0.026)	(0.019)	(0.027)
$Controls$	yes	yes	yes	yes	yes	yes	yes
SSC	0.006***	0.000***	0.003***	0.012**	0.002***	0.005***	0.006***
N	45,146	45,146	45,146	45,146	45,146	45,146	45,146
$Wald\ Test\ (\chi^2)$	3,694***	3,980***	3,778***	3,742***	3,781***	3,964***	3,715***

Notes: Table A8 reports the marginal partial effects from the estimation of $\Pr(y_{i,2} = 1|\mathbf{w}_i) = \Phi(\mathbf{w}_i\boldsymbol{\psi})$, where $\Phi(\cdot)$ is the CDF of the standard normal distribution, $\mathbf{w}_i$ is the vector of covariates and $\boldsymbol{\psi}$ is a vector of coefficients; $y_{i,2}$ is a binary variable that indicates whether the ith respondent's prediction is greater ($y_{i,2}$= 1) or lower ($y_{i,2}$= 0) than professional forecasters' mean prediction in the second interview. The vector $\mathbf{w}_i$ includes: the binary variable $y_{i,1}$, which indicates whether the ith respondent's prediction has been greater ($y_{i,1}$= 1) or lower ($y_{i,1}$= 0) than professional forecasters' mean prediction in the first interview; $NEWS_i^P$, which is an individual-specific indicator of news perception (which equals one if the interviewee has heard of changes in prices in the last few months before the interview and zero otherwise); $NEWS^N$ is an index of the intensity of news coverage of inflation in the New York Times and the Washington Post; $NEWS_{i,t}^{P,F}$ and $NEWS_{i,t}^{P,U}$ are individual-specific responses about the content of the news the survey participant has heard about; π, which denotes the last observed CPI inflation rate; π^F, which denotes the (twelve months-ahaed) mean forecast from the Survey of Professional Forecasters; a vector $\mathbf{x}_i$ of control variables, where we include information on the socio-demographic characteristics (such as gender, age, income, education, race, marital status, location in the US), as well as a number of interaction terms among them. To account for the presence of question attrition, we perform a sample selection correction test: SSC stands for the p-value of the Wald test of independence from the sample selection equation (which includes as regressors some socio-demographic characteristics as well as the tone of the news consumers have heard). A constant has been included in all regressions. Standard errors are calculated with the delta method (Oehlert, 1992) and are reported in parentheses. ***/**/* indicates significance at the 1/5/10% level.

Table A9: Determinants of the Forecast Bias at the Household-Level.

	Models Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
$y_{i,1}$	0.222*** (0.011)	0.211*** (0.010)	0.223*** (0.012)	0.230*** (0.013)	0.229*** (0.013)	0.219*** (0.011)	0.222*** (0.011)
π	0.000 (0.002)	0.012*** (0.002)	0.029*** (0.002)	0.030*** (0.003)	0.030*** (0.003)		
π^F			-0.075*** (0.005)	-0.077*** (0.005)	-0.077*** (0.005)		
$NEWS_i^P$	0.068*** (0.012)		0.065*** (0.012)		0.066*** (0.017)		0.068*** (0.016)
$NEWS^N$		-0.010*** (0.001)					
$NEWS_i^{P,U}$				0.080*** (0.014)			
$NEWS_i^{P,F}$				-0.054 (0.040)			
$NEWS_i^P \times y_{i,1}$					0.000 (0.024)	0.064*** (0.016)	-0.000 (0.022)
$Controls$	yes	yes	yes	yes	yes	yes	yes
SSC	0.000***	0.000***	0.000***	0.004**	0.004***	0.000***	0.000***
N	45,146	45,146	45,146	45,146	45,146	45,146	45,146
$Wald\ Test\ (\chi^2)$	2,758***	2,779***	3,242***	3,472***	3,437***	2,737***	2,758***

Notes: Table A9 reports the marginal partial effects from the estimation of $\Pr(y_{i,2} = 1|\mathbf{w}_i) = \Phi(\mathbf{w}_i\boldsymbol{\psi})$, where $\Phi(\cdot)$ is the CDF of the standard normal distribution, $\mathbf{w}_i$ is the vector of covariates and $\boldsymbol{\psi}$ is a vector of coefficients; $y_{i,2}$ is a binary variable that indicates whether the ith respondent's prediction is greater ($y_{i,2}$= 1) or lower ($y_{i,2}$= 0) than professional forecasters' mean prediction in the second interview. The vector $\mathbf{w}_i$ includes: the binary variable $y_{i,1}$, which indicates whether the ith respondent's prediction has been greater ($y_{i,1}$= 1) or lower ($y_{i,1}$= 0) than professional forecasters' mean prediction in the first interview; $NEWS_i^P$, which is an individual-specific indicator of news perception (which equals one if the interviewee has heard of changes in prices in the last few months before the interview and zero otherwise); $NEWS^N$ is an index of the intensity of news coverage of inflation in the New York Times and the Washington Post; $NEWS_{i,t}^{P,F}$ and $NEWS_{i,t}^{P,U}$ are individual-specific responses about the content of the news the survey participant has heard about; π, which denotes the last observed CPI inflation rate; π^F, which denotes the (twelve months-ahaed) mean forecast from the Survey of Professional Forecasters; a vector $\mathbf{x}_i$ of control variables, where we include information on the socio-demographic characteristics (such as gender, age, income, education, race, marital status, location in the US), as well as a number of interaction terms among them. To account for the presence of interview attrition, we perform a sample selection correction test: SSC stands for the p-value of the Wald test of independence from the sample selection equation (which includes as regressors some socio-demographic characteristics as well as the tone of the news consumers have heard). A constant has been included in all regressions. Standard errors are calculated with the delta method (Oehlert, 1992) and are reported in parentheses. ***/**/* indicates significance at the 1/5/10% level.

Appendix B: Pairwise Correlations

Table B1: Pairwise Correlations.

	$GAPSQ_t$	$GAPSQ_t^*$	$NEWS_t^N$	$NEWS_t^P$	$N_t^P N_t^N$	$NEWS_t^{P,F}$	$NEWS_t^{P,U}$	π_t
$GAPSQ_t$	1							
$GAPSQ_t^*$	0.537***	1						
$NEWS_t^N$	0.238**	0.026	1					
$NEWS_t^P$	0.604***	0.566***	0.071	1				
$N_t^P N_t^N$	0.718***	0.414***	0.567***	0.799***	1			
$NEWS_t^{P,F}$	-0.074	-0.071	0.216*	0.149	0.223*	1		
$NEWS_t^{P,U}$	0.626***	0.586***	0.017	0.973***	0.758***	-0.083	1	
π_t	0.535***	0.177*	0.752***	0.501***	0.787***	-0.029	0.512***	1

Notes: Table B1 reports pairwise correlations among the variables employed in the regression analysis of Section 3. $N_t^P N_t^N$ stands for $NEWS_t^P \times NEWS_t^N$. ***/**/* indicates significance at the 0.1/1/5% level.

Appendix C: Analysis with the Median Forecasts from the MS and the SPF

Table C1: Estimation of $\pi^C_{t+4|t} = \alpha_0 + \alpha_1 \pi^F_{t+4|t} + \alpha_2 \pi^C_{t+3|t-1} + \alpha_3 \pi_{t-1} + v_t$.

	Equations				
	1	2	3	4	5
α_0		0.066		0.048	
		(0.106)		(0.134)	
α_1	0.184***	0.180***	0.182***	0.180***	
	(0.044)	(0.045)	(0.044)	(0.045)	
α_2	0.812***	0.802***	0.838***	0.818***	1.027***
	(0.046)	(0.048)	(0.056)	(0.073)	(0.039)
α_3			-0.021	-0.011	-0.036
			(0.031)	(0.040)	(0.036)
Test	$\alpha_1 + \alpha_2 = 1$	$\alpha_0 = 0$	$\alpha_1 + \alpha_2 + \alpha_3 = 1$		$\alpha_2 + \alpha_3 = 1$
p-value	0.742	0.533	0.960		0.496
T	130	130	130	130	130
R^2	0.986	0.928	0.986	0.928	0.984

Notes: $\pi^C_{t+4|t}$ and $\pi^F_{t+4|t}$ are the (four quarters-ahead) median expectations from the Michigan Survey and the Survey of Professional Forecasters in period t, respectively; π_{t-1} is the most recently published annual inflation rate as of time t. Robust standard errors computed with the Huber-White sandwich estimator are reported in parentheses. ***/**/* indicates significance at the 1/5/10% level.

Table C2: Estimation of $GAP_t = \gamma_0 + \gamma_1 NEWS_t^N + \gamma_2 NEWS_t^P + \gamma_3 \left(NEWS_t^P \times NEWS_t^N \right) + \mu_t$.

	Equations							
	$GAPSQ_t$	$GAPSQ_t^*$	$GAPSQ_t$	$GAPSQ_t^*$	$GAPSQ_t$	$GAPSQ_t^*$	$GAPSQ_t$	$GAPSQ_t^*$
γ_0	0.134	1.924**	-0.013	-1.611**	-0.941**	-0.798	0.748	-1.346
	(0.385)	(0.794)	(0.261)	(0.793)	(0.426)	(0.823)	(0.556)	(1.261)
γ_1	0.101**	-0.016			0.079*	-0.065	-0.129*	0.002
	(0.048)	(0.049)			(0.044)	(0.076)	(0.070)	(0.106)
γ_2			0.231***	0.752***	0.237***	0.586**	0.001	0.662**
			(0.055)	(0.191)	(0.059)	(0.242)	(0.128)	(0.334)
γ_3							0.029*	-0.009
							(0.015)	(0.020)
T	123	122	131	130	123	122	123	122
R^2	0.041	0.000	0.220	0.383	0.432	0.357	0.500	0.358

Notes: GAP_t={$GAPSQ_t$,$GAPSQ_t^*$}, where $GAPSQ_t$ is the squared difference between the MS and SPF median inflation forecasts and $GAPSQ_t^*$ is the squared difference between the MS median inflation forecast and CPI inflation (at the forecast horizon); $NEWS_t^P$ is the fraction of MS participants that have heard of favorable or unfavorable changes prices in the period before the interview; $NEWS_t^N$ is an index of the intensity of news coverage of inflation in the New York Times and the Washington Post. Robust standard errors computed with the Huber-White sandwich estimator are reported in parentheses. ***/**/* indicates significance at the 1/5/10% level.

Table C3: Favorable and Unfavorable News, Expectation Updating and Forecast Accuracy.

Table C3(a)		Table C3(b)						
	$\pi^C_{t+4\|t}$		$GAPSQ_t$	$GAPSQ^*_t$	$GAPSQ_t$	$GAPSQ^*_t$	$GAPSQ_t$	$GAPSQ^*_t$
α_1^U	0.213***	γ_0	1.188***	3.162***	0.264	-0.883	0.006	-0.857
	(0.050)		(0.322)	(0.777)	(0.232)	(0.591)	(0.268)	(0.718)
α_1^F	0.191**	γ_1^F	0.128	-0.316			0.211	-0.021
	(0.076)		(0.156)	(0.324)			(0.159)	(0.264)
α_2^U	0.801***	γ_1^U			0.227***	0.779***	0.231***	0.778***
	(0.052)				(0.058)	(0.192)	(0.057)	(0.194)
α_2^F	0.732***							
	(0.084)							
T	130	T	131	130	131	130	131	130
R^2	0.987	R^2	0.004	0.004	0.210	0.406	0.220	0.406

Notes: Table C3(a) reports the OLS estimates of Equation (4); Table C3(b) reports the OLS estimates from Equation (5). Robust standard errors computed with the Huber-White sandwich estimator are reported in parentheses. ***/**/* indicates significance at the 1/5/10% level.